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ABSTRACT

A model for test scores called the profile analysis via multidimensional scaling (PAMS) model is described. The model reparameterizes the linear latent variable model in such a way that the latent variables can be interpreted in terms of profile patterns, rather than factors. The model can serve as the basis for exploratory multidimensional scaling analyses to identify major patterns in test scores; or it can serve as the basis for confirmatory structural equations analyses designed to test hypotheses about profile patterns and their associations with other variables. An exploratory multidimensional scaling analysis is described with particular emphasis on the interpretation of the model parameters in terms of latent profile patterns. The analysis is illustrated with vocational interest data. Finally, the exploratory multidimensional scaling analysis is compared to some alternative methods for identifying major profile patterns in data. (Contains 3 tables, 6 figures, and 23 references.) (Author)

# Profile Analysis via Multidimensional Scaling (PAMS): Exploring The Predominant Profile Patterns in Data

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Abstract

A model for test scores is described, a model called the profile analysis via multidimensional scaling (PAMS) model. The model reparameterizes the linear latent variable model in such a way that the latent variables can be interpreted in terms of profile patterns, rather than factors. The model can serve as the basis for exploratory multidimensional scaling analyses to identify major patterns in test scores; or it can serve as the basis for confirmatory structural equations analyses designed to test hypotheses about profile patterns and their associations with other variables. An exploratory multidimensional scaling analysis is described with particular emphasis on the interpretation of the model parameters in terms of latent profile patterns. The analysis is illustrated with vocational interest data. Finally, the exploratory MDS analysis is briefly compared to some alternative methods for identifying major profile patterns in data.

Profile Analysis via Multidimensional Scaling (PAMS): Exploring The Predominant Profile Patterns in Data

In past research, a variety of exploratory techniques have been used to identify profile patterns in a set of test data. These methods include various cluster analytic approaches (e.g. Konald, Glutting, McDermott, Kush, & Watkins,1999; Glutting, McGrath, Kamphaus, & McDermott, 1992), configural frequency analysis (e.g Stanton & Reynolds, 2001), and modal profile analysis (e.g. Skinner, 1979; Moses & Pritchard, 1995). This latter approach, modal profile analysis, is a hybrid of cluster analysis and Cattell's (1967) Q-factor analysis.

This paper outlines an exploratory multidimensional scaling based approach to identifying the major profile patterns in a set of data. The MDS approach, called Profile Analysis via Multidimensional Scaling (PAMS), is based on a linear latent variable model for test scores, a model that parallels the factor model in several respects. However, the PAMS model is a reparameterization of the linear latent variable model so as to address research questions about profile patterns. Thus, rather than describing a totally new model, this paper describes how to reparameterize a familiar model so as to address a different set of questions. An analysis based on the model will be illustrated with a set of vocational interest data.

The analysis described in this paper is purely exploratory. Two related papers (Kim and Davison, 2001a,, Ding, Sackett, Blake, & Davison, 2001) attempt to translate the model into structural equations form so as to yield confirmatory analyses for testing hypotheses about profile patterns. In actual application, the hypotheses will often involve profile patterns uncovered by exploratory methods like the one described here.

In comparing the exploratory approach in this paper with others in the literature, there are three major features of this analysis to keep in mind. All three of these features will be described in more detail below. First, the model includes the Q-factor model as a special case. Furthermore, unlike methods based on the Q-factor approach, the MDS analysis described here can readily be applied to samples of any size. Second, the MDS analysis is designed for the study of individual differences in profile patterns distinct from individual differences in profile levels. Researchers who do not wish to separate these two kinds of individual differences (profile level vs. pattern) will prefer other analyses. Thirdly, whereas cluster analysis and configural frequency analysis describe people in terms of discrete groupings, the PAMS approach describes people in terms of continuous profile match parameters. That is, people are assumed to vary in the extent to which their actual profiles match each of several "prototypical" profiles.

Before introducing the model, let me define a term already used several times: profile pattern. For our purposes, a profile is simply a set of scores on a test battery. Each row of data in Figure 1 is a profile of scores. The mean score in a profile is called the profile level or profile elevation. That is, the mean score in row 1 is the level of the first profile in Figure 1; the mean of row 2 is the level of the second profile in Figure 1; etc. Profile pattern refers to the scores in a row after subtracting the row mean from each. That is, the profile pattern means the scores in the row expressed as deviations about the row mean. The scores in a profile pattern are said to be ipsative because they sum to zero for each person.

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Insert Figure 1 here.

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We now turn to a description of the PAMS model and the analysis based on that model.

## PAMS Model and Analysis

The PAMS model can often best be explained by contrasting it with the factor or components model. The basic assumption of the factor model is that we can posit a small set of latent column variables, represented by the columns of dots in Figure 1, such that the observed column variables can be accounted for as linear combinations of the latent ones. We can do the same thing by rows. Each row of the data matrix constitutes a profile. We can posit a small set of latent profiles, represented by the rows of dots in Figure 1, such that the observed profiles can be accounted for as linear combinations of the latent ones. This leads to a model that is linear, and hence belongs to the class of linear latent variable models:

$$\underline{m}_{pt} = \underline{c}_p + \Sigma_k \underline{w}_{pk} \underline{x}_{tk} + \underline{e}_{pt} \qquad (1)$$

Here $\underline{m}_{pt}$ designates an observed data point, the score of person $\underline{p}$ on test $\underline{t}$; that is, the element in row $\underline{p}$ and column $\underline{t}$ of the data matrix. The parameter $\underline{c}_p$ equals the mean score in row $\underline{p}$; that is, $\underline{c}_p$, indexes the overall elevation of person $\underline{p}$'s profile, and it is hereafter called the level parameter.

Each term in the sum on the right side of Equation 1 refers to a latent profile pattern $\underline{k}$. Since latent profiles will later correspond to multidimensional scaling (MDS) dimensions, one can think of $\underline{k}$ as designating either a latent profile pattern or the corresponding MDS dimension. Each term in the sum is the product of a person parameter, $\underline{w}_{pk}$, and a test parameter, $\underline{x}_{tk}$. The test parameter, $x_{tk}$, equals the score of test $t$ in latent profile $k$. The person parameter, $w_{pk}$, is a weight for person $p$ and latent profile $k$. Also, one can think of $w_{pk}$ as a measure of profile match that indexes the degree of match between the actual profile of person $p$ and the latent profile $k$. Finally, $e_{pt}$ is an error term representing measurement error and systematic deviations from the model.

Although the profile interpretation of Equation 1 has seldom been utilized, the model is not new. Bechtel, Tucker, and Chang (1971), Davison (1994), Davison and Skay (1991), and Tucker (1960) call it the "vector" model. The French statistician Benzecri (1969), Weller and Romney (1990), and Greenacre (1984) call it the "correspondence analysis" model. Cattell's (1967) Q-factor model is a special case of Equation 1 in which the observed data are standardized by row and $c_p$ drops from the model because it equals zero for every person $p$.

Assumptions and restrictions. To develop the estimation method, we first need to add some assumptions and restrictions that uniquely identify the parameters:

$$\Sigma_t x_{tk} = 0.0 \quad \text{for all } k \tag{2}$$

$$(1/P)\Sigma_p w_{pk}^2 = 1.0 \quad \text{for all } k \tag{3}$$

$$\Sigma_p w_{pk} w_{pk'} = 0 \text{ for all } (k, k') \tag{4}$$

$$(1/P)\Sigma_p e_{pt} = 0 \quad \text{for all } t \tag{5}$$

$$(1/P)\Sigma_p e_{pt}^2 = \sigma^2 \quad \text{for all } t \tag{6}$$

and

$$\Sigma_p w_{pk} e_{pt} = 0 \quad \text{for all } (k, t) \tag{7}$$

Here $\underline{P}$ refers to the number of people in the data matrix and $\sigma^2$ equals the variance of the deviations, $\underline{e}_{pt}$, in Equation 1. For the most part, Equations 2 - 7 are variations on standard assumptions and side conditions. Equation 2 should be noted, because it states that each latent profile, $\underline{k}$, is ipsative; that is, the mean of the scores in each latent profile equals zero. Consequently, latent profiles will reproduce observed profile patterns (scatter plus shape), but not the level of observed profiles which is reproduced by the level parameters $\underline{c}_p$. Equation 6 implies that the deviation variances are equal for all tests. This is an unduly strong assumption, but one that seems necessary to justify the kinds of scaling analyses most commonly available in existing statistical packages. These readily available analyses are the ones employed in most of the published studies applying MDS to test intercorrelations.

Several features of the model deserve highlighting because they become important for purposes of specifying the model in the structural equations framework of Kim and Davison (2001a) and Ding, Sackett, Blake, and Davison (2001). First, in addition to K latent variables corresponding to dimensions, the structural equations form includes one additional latent variable to account for individual differences in profile level. Thus, the structural equations form contains K+1 latent variables when there are K latent profile patterns.

Second, along the "extra" K+1[st] latent variable, the test parameters are all constrained to be equal. To understand why, imagine that the first term on the right of Equation 1 is written $1.00c_p$. The term, $1.00c_p$, is the product of a person parameter, $c_p$, and a test parameter, 1.00. The test parameter, the implied multiplier "1" is a constant across tests. Thus, along the extra K+1[st] variable in the structural equations form of the model, a test parameter is specified for each test and it is constrained to be a constant across tests, although it is not constrained equal to 1.00.

Third, along the K latent variables corresponding dimensions, the test parameters are constrained to satisfy the restriction in Equation 2 above. That is, the test parameters are constrained to sum to zero.

Therefore, in the Kim and Davison(2001a) and Ding et. al. (2001) papers, the authors will add a K+1st latent variable to account for individual differences in profile level. They will constrain the test parameters along that K+1st latent variable to be equal. Along the remaining K latent profile variables, the sum of test parameters will be constrained to equal 0, the constraint in Equation 2.

Estimation of Parameters. As described by Davison and Skay (1991) and Davison (1996), Equations 1 - 7 lead to the following result concerning the squared euclidean distance proximity measure defined over all possible pairs of tests, a result on which parameter estimation can be based:

$$\delta_{tt'}^2 = (1/P)\Sigma_p(m_{pt} - m_{pt'})^2 \tag{8}$$

$$= \Sigma_k(x_{tk} - x_{tk'})^2 + 2\sigma^2 \tag{9}$$

$$= d_{tt'}^2 + 2\sigma^2$$

As shown in Equation 9, under the assumptions of Equations 1 - 7 (Davison, 1996) and except for an additive constant, $2\sigma^2$, $\delta_{tt'}^2$ will equal the squared Euclidean distance between pairs of tests ($t$, $t'$) expressed in terms of the test parameters in the model of Equation 1, $\underline{x}_{tk}$. This implies that the squared Euclidean distance proximity measure satisfies the fundamental assumption of common MDS analyses. Hence, we can estimate the test parameters in the model by computing the squared Euclidean distance matrix for all possible pairs of tests and submitting that matrix to an MDS analysis. The squared Euclidean distance proximity measure can be found in standard statistical packages. The MDS analysis should yield one dimension for each latent profile. Along a given dimension $\underline{k}$, the scale value for test $\underline{t}$ along dimension $\underline{k}$ is our estimate of the score for test $\underline{t}$ in latent profile $\underline{k}$, $\underline{x}_{tk}$.

This leads to an analysis that very closely parallels factor analysis. As in factor analysis, the first step is to compute a proximity matrix. Whereas in factor analysis, the proximity matrix is a covariance matrix or correlation matrix, in MDS it would be a squared Euclidean distance matrix or a correlation matrix. When the observed variables are in standardized form, the squared Euclidian distances will be monotonically related to the correlation coefficients. Therefore, in a nonmetric MDS, we would get the same solution using either squared Euclidean distances or correlation coefficients, and that solution provides estimates of the test parameters in our model.

As with factor analysis, the second step is to submit the proximity matrix to an analysis that will yield estimates of the test parameters in our model. In the case of factor analysis, any of several well known algorithms have been used to estimate the test parameters, the factor loadings. For the MDS analysis, the squared Euclidean distances (or correlations) would be submitted to an MDS analysis. If the assumptions of the model are satisfied, the analysis should yield one dimension for each latent profile. Along dimension $\underline{k}$, the scale value $\underline{x}_{tk}$ will be our estimate of the score for test $\underline{t}$ in latent profile $\underline{k}$.

Whether applying factor analysis or MDS, the third step involves estimating the person parameters, factor scores in factor analysis and person correspondence weights $\underline{w}_{pk}$ in MDS.

Roughly speaking, each person parameter $\underline{w}_{pk}$ will index the correspondence between the actual profile of subject p and the latent profile k. SAS and SPSS code for estimating the parameters in equation 1 is available in Davenport, Davison, Bielinski, and Ding (1995).

## Vocational Interest Example

This example involves the Basic Theme Scales from the Strong-Cambpell Interest Inventory (Campbell & Hansen, 1985): the Realistic, Investigative, Artistic, Social, Enterprising and Conventional interest scales. Holland (1973) proposed a two-dimensional, hexagonal model for these six scales. While Holland has been reluctant to name the two dimensions, others have labeled them People vs. Things and Data vs. Ideas (Prediger, 1982; Tracey & Rounds, 1993). The data for this example were collected by Rene Dawis and David J. Weiss from 1308 males who were clients of the Vocational Assessment Clinic at the University of Minnesota. Table 1 shows the intercorrelations of the six scales.

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Insert Table 1 here.
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### Interpreting Test Parameter Estimates

Table 2 and Figure 2 show the two-dimensional solution resulting from a nonmetric MDS analysis of these correlations. Dimension 1 looks like Prediger's (1982) Data vs. Ideas Dimension. According to theory, the Data end of the dimension should be marked by the Enterprising and Conventional scales that fall at the positive end of Dimension 1. The Ideas end should be marked by the Artistic and Investigative scales. Both fall at the negative end of Dimension 1, although the Investigative scale does not fall as far toward the negative end as theory would lead one to expect.

Insert Table 2 and Figure 2 here

According to theory, the People end of the People vs. Things dimension should be marked by the Social and Enterprising scales that fall at the negative end of Dimension 2. The Things end should be marked by the Realistic and Investigative scales falling at the positive end of Dimension 2.

Plotting the scale values as profiles reveals the pattern sketched by the scale values along each dimension. In Figure 3, each Basic Theme Scale has been plotted along the horizontal axis. Above each Basic Theme Scale, its Dimension 1 scale value has been plotted along the vertical axis. Figure 3 shows a profile with elevated scores on the Enterprising and Conventional scales and one notably low score, Artistic A client with this profile would rather work with data than with ideas. If one were to label this profile in terms of high point codes following a reasonably common convention in the assessment literature, it would be called the Enterprising/Conventional or E/C profile.

Insert Figure 3 here.

Figure 4 shows the profile pattern sketched by the scale values along Dimension 2. Each Basic Theme Scale has been plotted along the horizontal axis, and above it, Figure 4 contains the Basic Theme Scale's Dimension 2 scale value plotted on the vertical axis. This profile is marked by elevated scores on the Realistic and Investigative scales and by depressed scores on the Social and Enterprising scales. A client with this profile would rather work with things than with people. If it were labeled in terms of high point codes, it would be called a

Realistic/Investigative or R/C profile. Taken together, Dimensions 1 and 2 constitute a spatial representation of the major profile patterns in the data matrix as recovered by MDS.

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Insert Figure 4 here.
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Interpreting Person Parameter Estimates

Having interpreted the test parameter estimates, let's look at person parameters for eight of the 1308 people in this data matrix as shown in Table 3. The first two columns contain a rescaling of the person parameters, $w_{pk}$. Multiplying $w_{pk}$ by the standard deviation of the scale values along dimension k, $s_k$, we get a quantity $v_{pk} = s_k w_{pk}$ whose absolute value equals the square root of the variance in the profile of person p accounted for by dimension k if the dimensions are orthogonal. When the dimensions are orthogonal, $\underline{v}_{pk}$ equals the covariance between the scores in observed profile p and the scale values along dimension k after rescaling the scale values along dimension k to have standard deviation 1. The sign of $\underline{v}_{pk}$ indicates whether the profile of person p resembles dimension profile k (positive sign) or the mirror image of dimension profile k (negative sign). This value $v_{pk}$ is our profile match index indicating the direction and magnitude of match between the observed profile of person p and the latent profile dimension k.

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Insert Table 3 here.
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Column 1 of Table 3 contains the person parameters, $v_{p1}$. Some Dimension 1 person parameters, such as that for Case 164, are positive indicating a trend in the client's profile similar to the Dimension 1 pattern. Some, such as that for Case 005, are negative indicating a trend in the client's profile that is the mirror image of the Dimension 1 pattern. Still others are near zero, such as Case 202, indicating little or no linear trend in the client's profile similar to the Dimension 1 pattern. Column 2, labeled $v_{p2}$ contains the Dimension 2 profile match parameters.

Column 3, labeled $\underline{c}_p$, contains the estimate of each client's level parameter. The data in this example were standardized to have mean zero, so positive level parameters, such as that of Case 164, suggest a profile that is more elevated than that of the average client in the data file. Negative level parameters, such as Case 002, suggest a profile that is more depressed than that of the average client in the data file.

The last column, labeled R squared, contains a squared multiple correlation indicating the proportion of variance in the client's observed profile accounted for by the two MDS dimensions. Some client's data are accounted for quite well, such as that of Case 002 for whom $\underline{R}^2 = .95$. Other observed profiles, such as that of Case 003, are not well accounted for: $\underline{R}^2 = .21$. The average $\underline{R}^2$ in this data file was .57.

To see the relationship between client profile match parameters and actual client profiles, let's look at some actual client profiles. First, consider Case 164. This client's profile is well accounted for, $\underline{R}^2 = .95$. The level parameter is positive, .70, indicating that his profile is somewhat elevated compared to that of the average client. The profile match statistic for Dimension 2, $\underline{v}_{p2}$, is essentially zero. Dimension 1 alone accounts for most of the variation in this client's profile. This suggests that the pattern of this client's profile is very similar to that of Dimension 1.

Figure 5 shows this client's actual profile. The elevated nature of the profile is reflected by the fact that five of the client's six scores fall above the zero point on the vertical axis. Like the Dimension 1 profile shown in Figure 3, Case 164 has elevated scores for the Enterprising and Conventional scales and notably low scores on the Artistic scale.

As a second example, consider Case 202 in Table 3. Again, the two dimensions account for this client's data quite well: $\underline{R}^2 = .96$. The level parameter, .30, indicates a somewhat elevated profile as compared to the average client. The Dimension 2 profile match index, $\underline{v}_{pk}$, is far larger than that for Dimension 1, indicating that this client's data is accounted for largely by Dimension 2. However, the Dimension 2 profile match parameter is negative, indicating that the client's observed profile is the mirror image of the Dimension 2 pattern.

Figure 6 shows the observed profile for Case 202. Whereas the Dimension 2 profile, Figure 4, shows elevated scores on the Realistic and Investigative scales, these are the two lowest scores in Figure 6. Whereas the Case 202 profile, Figure 6, has elevated scores on the Social and Enterprising scales, these are the lowest scores along Dimension 2 of Figure 4. The Dimension 2 profile of Figure 4 is indeed a mirror image of Client 202's actual profile in Figure 6.

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Insert Figures 5 and 6 here.
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The person parameters, $\underline{w}_{pk}$, are computed much like factor scores. That is, they are computed by regressing each person's observed scores onto the dimension scale values. Essentially, this is a within person multiple regression with the client's profile of scores as the criterion variable and the $\underline{K}$ dimensions as the predictor variables. Unlike factor scores, however, the parameters $\underline{w}_{pk}$, are used to estimate the person profile match indices $\underline{v}_{pk}$. These indices signify the direction and magnitude of the match between the actual profile of client p and the dimension profile k.

## Discussion

Profile Analysis via Multidimensional Scaling is a purely exploratory technique designed to identify the major profile patterns appearing in a set of data. It includes a method of quantifying the direction and magnitude of the match between the major profile patterns and the actual score profiles of clients. Results of the analysis can prove interesting in their own right. In many cases, however, the exploratory results from a PAMS analysis will only serve as a first step. That is, the patterns initially identified in an exploratory PAMS analysis may be used later in confirmatory analyses of the kind illustrated by Kim and Davison (2001a). Patterns identified by PAMS may also be used in later regression (e.g. Kuang, 1998) or structural equations modeling (e.g., Ding, Sackett, Blake, and Davison, 2001) to study the association between profile patterns and criterion variables external to the test battery from which the profile patterns were derived.

The model on which PAMS is based includes the Q-factor model as a special case. Therefore, PAMS is more flexible. Furthermore, because it begins with an analysis of a tests-by-tests proximity matrix, rather than a persons-by-persons matrix, the PAMS approach is simpler to implement with large samples. While not shown here, Kim and Davison (2001b) have devised a bootstrapping technique for estimating standard errors of parameters in the PAMS model, a method that requires no assumptions about the distribution of the data. While it is computationally laborious, the recent advances in computer speed and memory have made the bootstrapping procedure quite feasible. Further advances in computer technology will make it even more so.

In this paper, we estimated the parameters in the model using the most common, nonmetric multidimensional scaling analyses found in most major computer packages. Unfortunately, this particular approach seems to require an assumption that all tests in the battery have equal error variances. For the tests in many published batteries, this assumption may be reasonably met. When the assumption is not met, correspondence analysis may provide estimates of the parameters in the model without making the assumption of equal error variances. We say "may provide" because we have not formally examined the assumptions under which correspondence analysis will provide the desired parameter estimates. To obtain the proper solution, however, the user must ensure that the correspondence analysis is implemented so as to place the origin of the solution at the centroid of the tests.

The suitability of this PAMS approach depends, in part, on how the research questions are framed. This "PAMS" analysis separates profile level from profile pattern for the purpose of focusing on the major profile patterns. In some cases, the researcher may not wish to study individual differences in profile pattern separate from individual differences in profile level. In such cases, other approaches would be preferred. When the researcher does want to focus on patterns, a PAMS analysis can provide an exploratory first step leading to subsequent confirmatory analyses or subsequent studies of the association between patterns and criterion variables.

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Table 1

Interest Inventory Intercorrelations among Males: Minnesota Vocational Assessment Clinic Data (N = 1308)

| | Real | Inves | Art | Social | Eat | Conv |
|---|---|---|---|---|---|---|
| Realistic | 1.00 | 0.52 | 0.06 | 0.18 | 0.30 | 0.37 |
| Investigative | 0.52 | 1.00 | 0.33 | 0.32 | 0.13 | 0.37 |
| Artistic | 0.06 | 0.33 | 1.00 | 0.26 | 0.01 | -0.09 |
| Social | 0.18 | 0.32 | 0.26 | 1.00 | 0.38 | 0.34 |
| Enterprising | 0.30 | 0.13 | 0.01 | 0.38 | 1.00 | 0.46 |
| Conventional | 0.37 | 0.37 | -0.09 | 0.34 | 0.46 | 1.00 |

Data collected by David J. Weiss and Rene Dawis, University of Minnesota, Vocational Assessment Clinic

Table 2

Two-Dimensional MDS Solution based on SCII Intercorrelations ($x_{tk}$)

| Scale | Dimension 1 | Dimension 2 |
| --- | --- | --- |
| Realistic | 0.11 | 1.21 |
| Investigative | -0.25 | 0.96 |
| Artistic | -2.14 | -0.05 |
| Social | -0.07 | -1.14 |
| Enterprising | 1.09 | -0.94 |
| Conventional | 1.26 | -0.03 |

Table 3

Person Parameters for Eight People: SCII Profiles

| Client | Dim. One Cor. Wt. $v_{p1}$ | Dim. Two Cor. Wt. $v_{p2}$ | Level Param. $c_p$ | R Squared |
|---|---|---|---|---|
| 001 | 0.32 | 0.25 | -0.06 | .48 |
| 002 | -1.02 | -0.39 | -1.15 | .95 |
| 003 | 0.24 | -0.19 | -0.65 | .21 |
| 004 | -0.61 | 0.12 | 0.13 | .70 |
| 005 | -1.22 | -0.37 | 0.35 | .74 |
| 164 | 0.95 | 0.01 | 0.70 | .95 |
| 202 | 0.18 | -1.07 | 0.30 | .96 |
| 234 | 0.21 | 1.09 | -1.30 | .95 |

## Figure Captions

Figure 1. Persons by Tests Data Matrix with Latent Factors and Latent Dimension Profiles

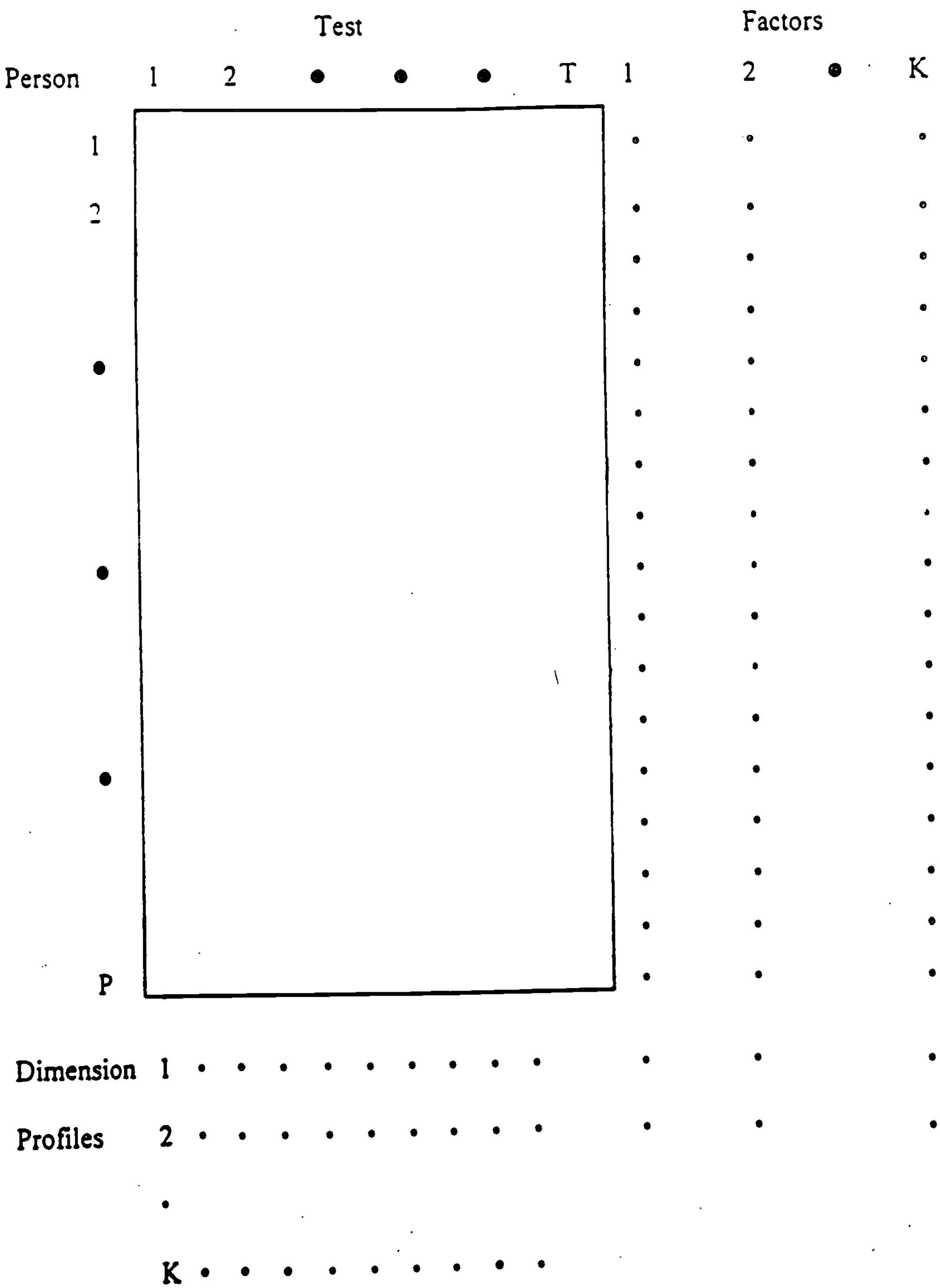
Figure 2. Vocational Interest Dimension 1 vs. Dimension 2

Figure 3. Data vs. Ideas Dimension

Figure 4. People vs. Things Dimension

Figure 5. Profile of Client 164

Figure 6. Profile of Client 202


Test
Factors
Person
1
2
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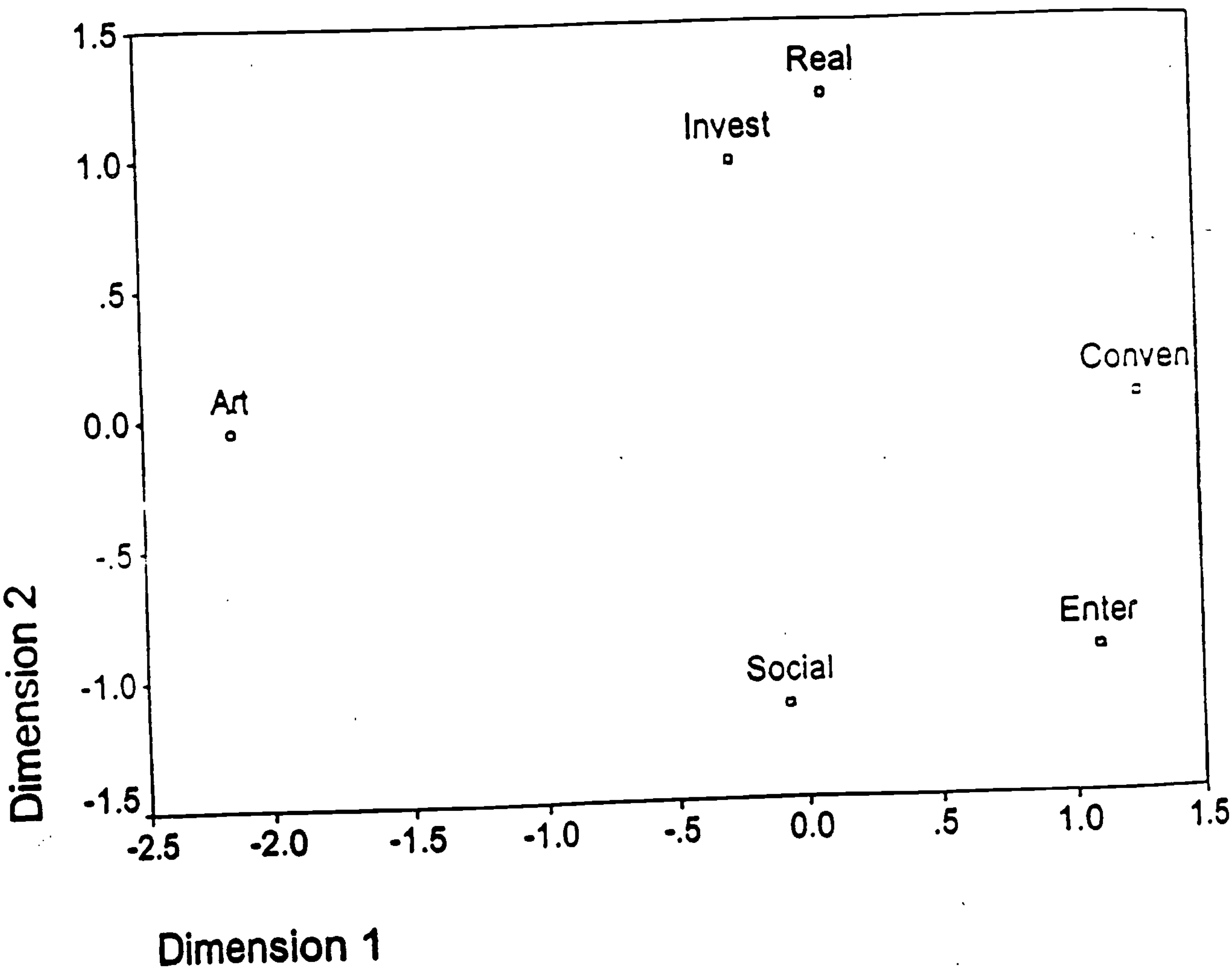
Dimension 1
Profiles 2
K


Real
Invest
Conven
Art
Enter
Social
1.5
1.0
.5
0.0
-.5
-1.0
-1.5
-2.5
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-1.5
-1.0
-.5
0.0
.5
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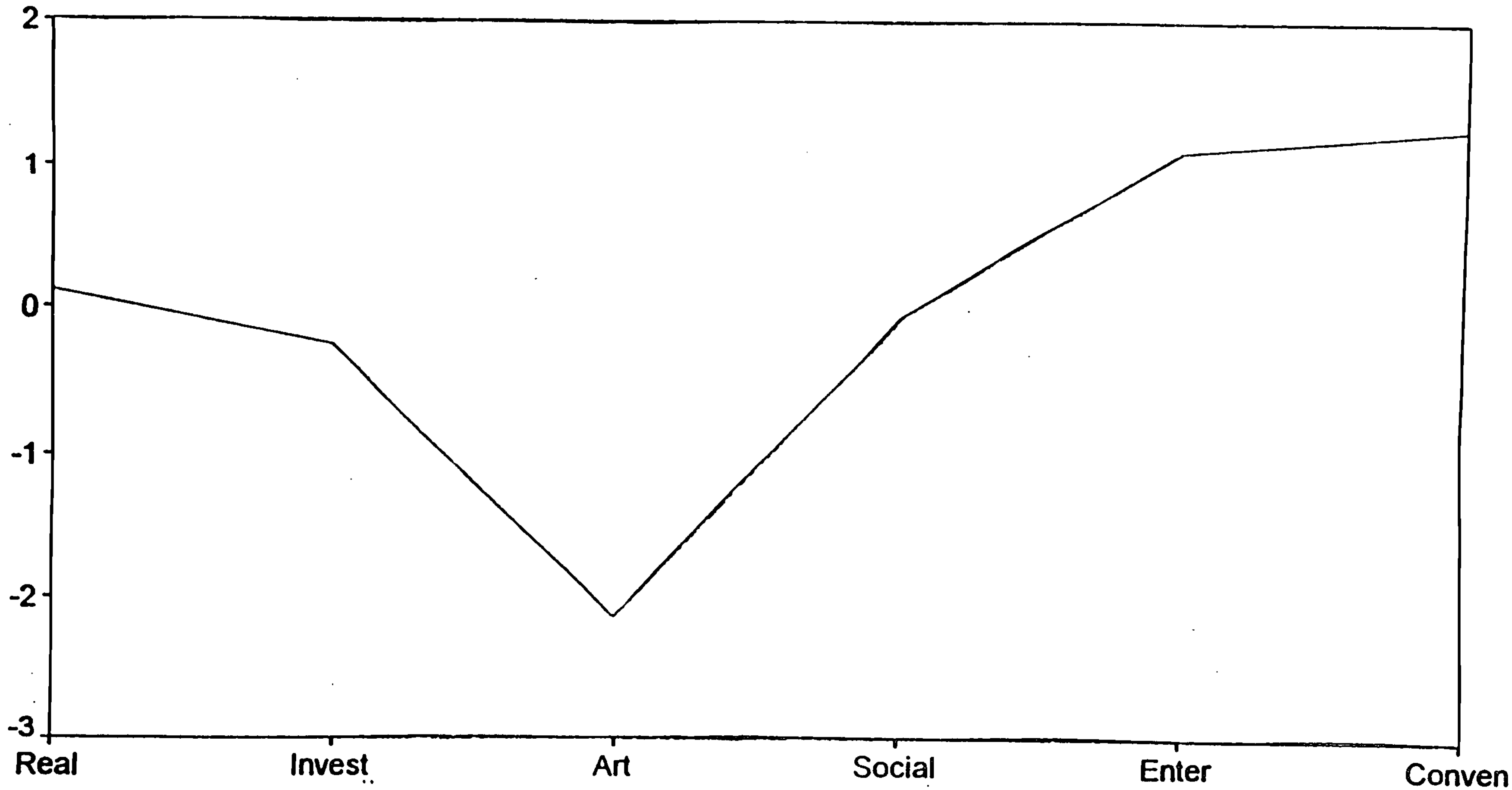
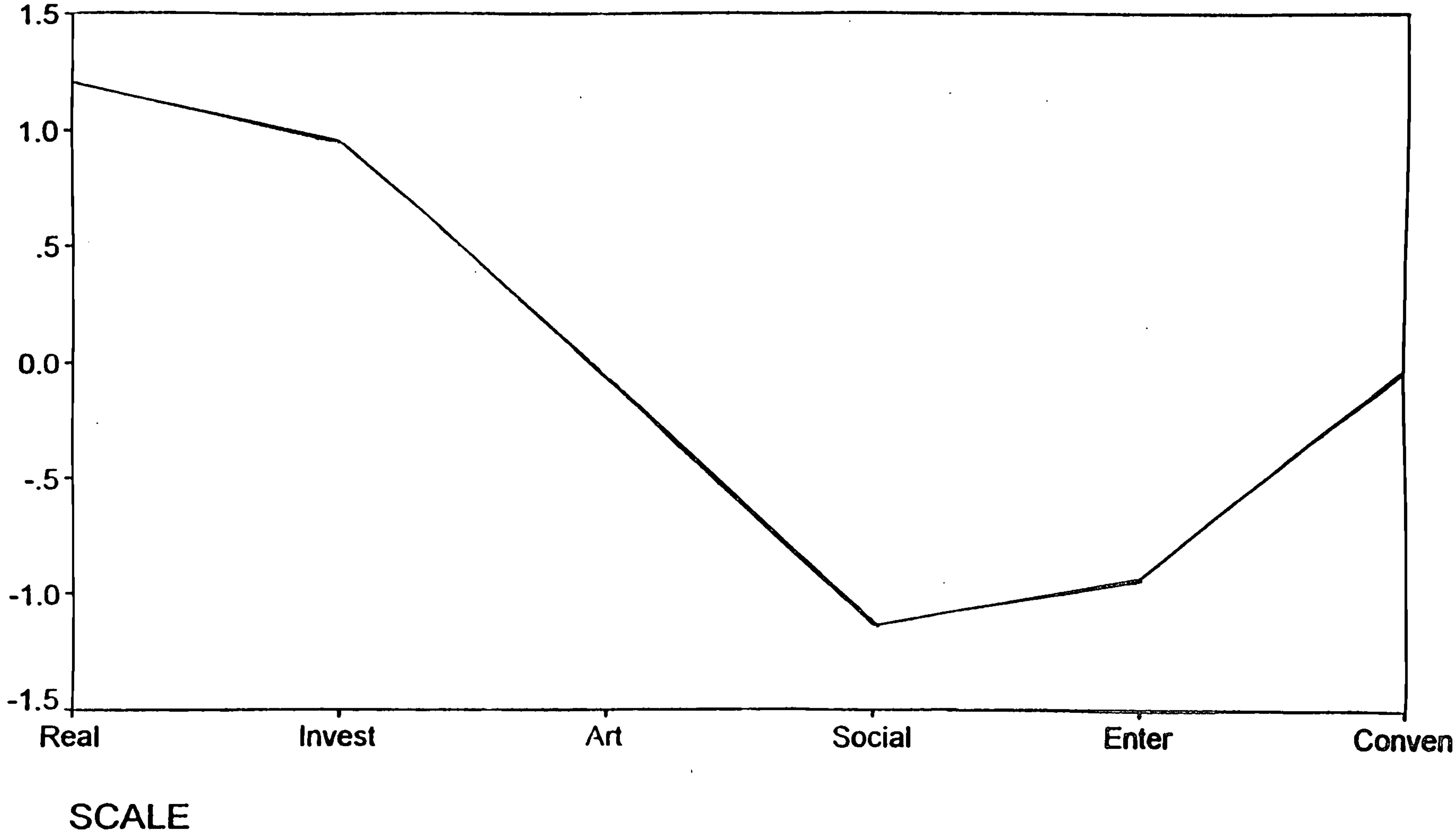
1.5
Dimension 2
Dimension 1




SCALE

27


1.5
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0.0
-.5
-1.0
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Real
Invest
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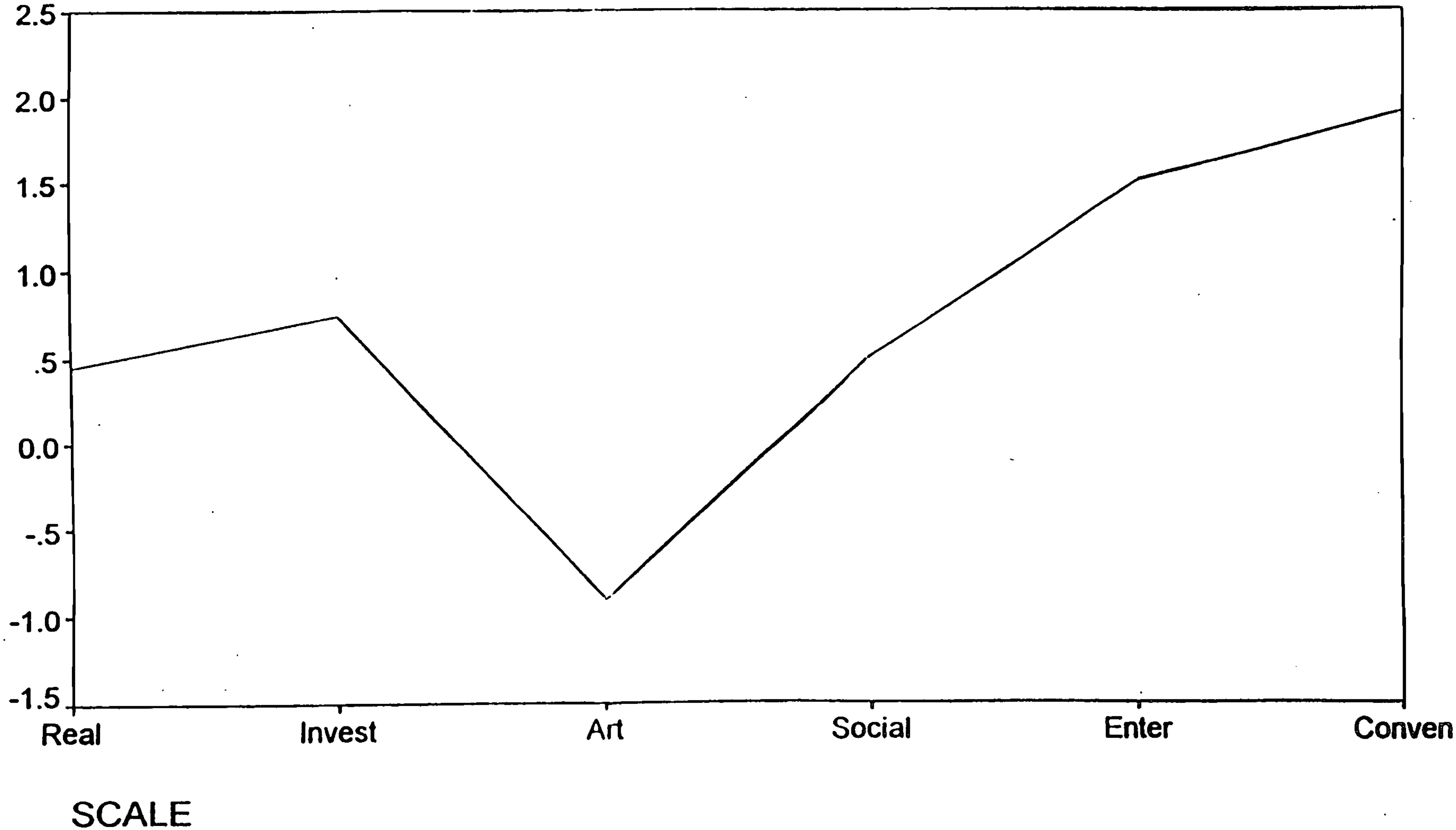
SCALE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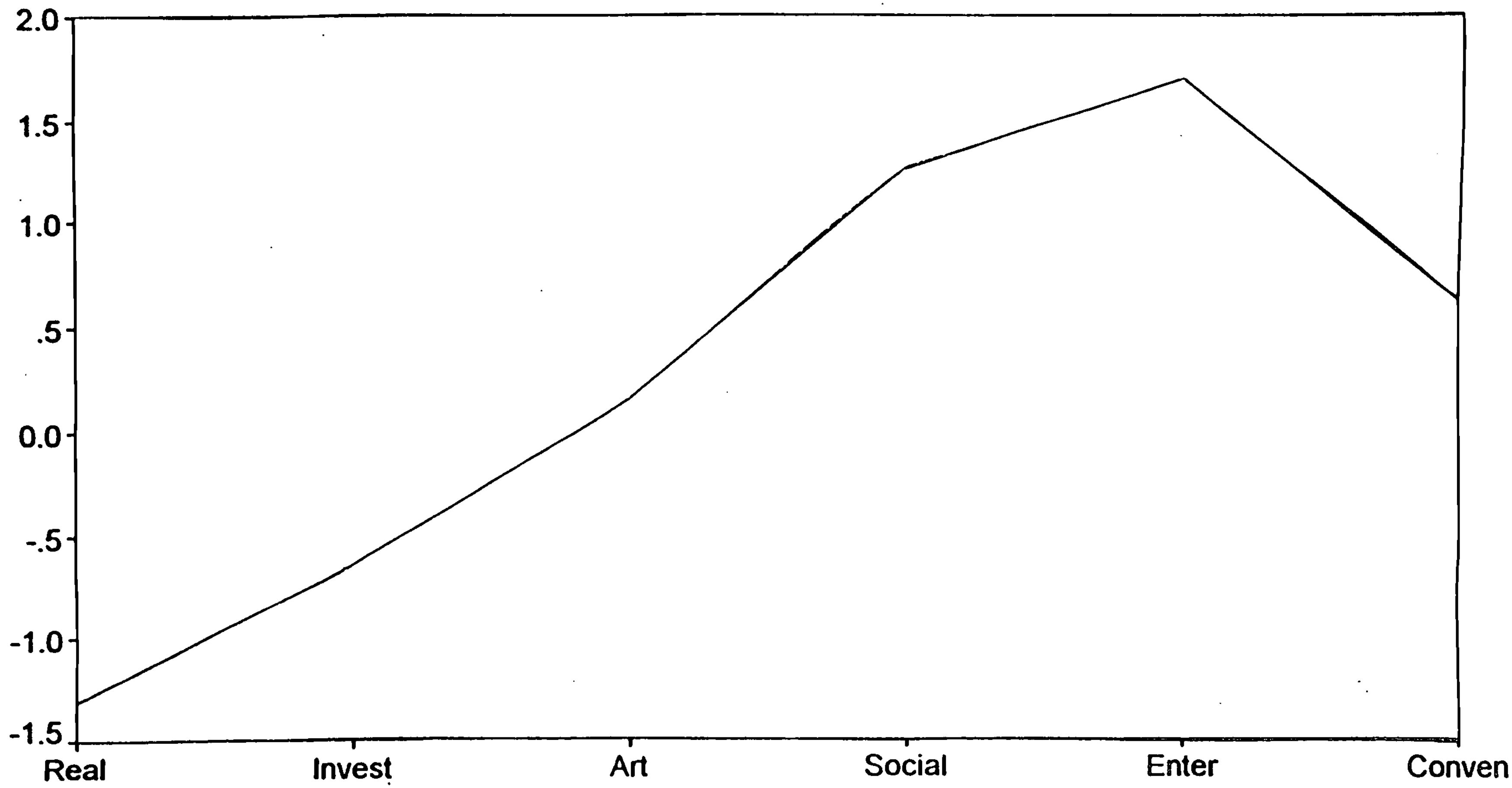
2.0
1.5
1.0
.5
0.0
-.5
-1.0
-1.5
Real
Invest
Art
Social
Enter
Conven
SCALE

31

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